Who is a Passive Saver Under Opt-In and Auto-Enrollment?*

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August 30, 2018

Abstract

Defaults have been shown to have a powerful effect on retirement saving behavior yet there is little research addressing why defaults work or whether default regimes influence the characteristics of those who passively accept the default. Using administrative data on employer-sponsored retirement accounts linked to survey data, we estimate the relationship between retirement saving choices and individual characteristics – present bias, financial literacy, and exponential-growth bias – under an opt-in regime and an auto-enrollment regime. In contrast to a previous literature which has assumed passivity is associated with a fixed behavioral type, we find that the determinants of passive behavior are regime-specific. Under the opt-in regime, financial literacy plays an important role in predicting total contributions, active saving choices, and maxing out contributions in the tax-preferred account. In contrast, under the auto-enrollment regime, present bias is the most significant behavioral predictor of saving outcomes. Results remain robust after correcting for measurement error using an instrumental-variables technique. A causal interpretation of the estimates suggests that auto-enrollment increases saving primarily among those with low financial literacy.

*Acknowledgments: This research was supported by the U.S. Social Security Administration through grant #RRC08098400-09 to the National Bureau of Economic Research (NBER) as part of the SSA Retirement Research Consortium, by the TIAA Institute through grant #124652, and the Laura and John Arnold Foundation through a grant to the Stanford Institute for Economic Policy Research (SIEPR). The findings and conclusions expressed are solely those of the authors and do not represent the views of SSA, any agency of the Federal Government, the NBER, TIAA/TIAA Institute, the Laura and John Arnold Foundation, SIEPR or any other institution with which the authors are affiliated. We are grateful to Paula Gablenz and Konhee Chang for exceptional research assistance.
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Keywords: present bias, exponential-growth bias, household finance; retirement saving decisions; choice architecture; defaults; financial literacy; procrastination.

1 Introduction

A large body of research on employer-provided retirement plans has shown that the default has a strong influence on saving behavior as many individuals passively accept the default (Madrian and Shea, 2001; Choi et al., 2004; Beshears et al., 2009). Other research has shown that passive choice can have important consequences both for the overall effectiveness of policy as well as its distributional consequences (Chetty et al., 2014). Much less is known about what mechanisms lie behind the default effect or, put another way, whether who is passive is invariant under different regimes. Because default provisions are a key feature of widespread, employer-provided retirement savings plans, these questions have broad implications for the well-being of many aging workers.

The classical life-cycle model predicts that defaults should almost always have no effect on retirement saving behavior. Even when transaction costs are required to make a change, the benefits of having an optimal contribution rate will almost always dwarf the relatively-minor inconvenience of filling out paper work. However, two main classes of explanations inform potential mechanisms behind the strong "default effect." First, procrastination induced by present-biased preferences is a leading theoretical candidate (O'Donoghue and Rabin, 1999a,b; Beshears et al., 2009; Bernheim et al., 2015). Under an opt-in regime, transaction costs are immediate but the benefits of changing one's contribution are in the distant future. A naïve procrastinator may expect to make the change in the near future but delay indefinitely.

A second potential mechanism leading to passive behavior may be a lack of ability to make optimal saving decisions. For instance, many Americans have low levels of financial literacy (Lusardi and Mitchell, 2014) and employees with less understanding may avoid making an active decision until they feel that they have sufficient understanding. In addition, people may underestimate the cost of delaying action when their preferences do not align with the terms of the default. In this paper, we model this channel through exponential-growth bias (EGB), whereby people partially linearize compound growth (Stango and Zinman, 2009; Levy and Tasoff, 2016; Goda et al., 2015).

Combining these two ideas, the model of Carroll et al. (2009) exhibits agents with present-biased preferences and heterogeneity in their long-run optimal savings rate. The choice to passively accept the default then depends on how close the default is to the person's optimal savings rate. This implies that different kinds of people should be passive under different default regimes.

Though present bias (PB), financial literacy, and EGB are all plausible mechanisms for the powerful effect of defaults, alternative mechanisms could also explain the default effect. For instance, employees may view the default as an endorsement from their employer or the default may serve as a salient anchor (Tversky and Kahneman, 1975; Ariely et al., 2003). In addition, recent research shows that limited attention can lead to sticky behavior (Sims, 2003; Gabaix, 2014) and may also lead to unawareness that a choice is available. A possible implication of unawareness is that a stable sample of employees would remain passive savers independent of the default regime.

Which mechanisms explain the effects of defaults on retirement savings defaults has direct implications for welfare and policy. Identifying the particular mechanism can inform the types of policies or interventions that may improve welfare. If the stickiness of defaults is due to a perceptual bias, interventions that mitigate that bias can be welfare-improving. If, by contrast, saving choices are orthogonal to these biases, addressing these biases will do little to change saving outcomes or improve welfare.

In this paper, we examine the relationships between present-biased preferences, financial illiteracy, and EGB with saving choices in an employer-provided retirement plan. Our approach combines administrative records on employee contribution behavior with direct, survey-based elicitations of PB, EGB, and financial literacy. We evaluate how these measures predict retirement saving behavior: the failure to make an active choice, saving at default contribution rates, making any contribution, contributing to maximize the employer match, and contributing the annual maximum allowed to take full advantage of this tax-preferred saving opportunity. More importantly, we are able to exploit a change in the default regime to evaluate the relationship between these measures and saving behavior separately across opt-in and auto-enrollment regimes.

Our data come from employees at the U.S. Office of Personnel Management (OPM), an agency that provides human resources, leadership, and support to most federal agencies. We analyze choices pertaining to the Thrift Savings Plan, a supplementary defined contribution tax-preferenced savings plan. We control for a rich set of covariates relevant to contribution decisions, including salary, demographics and education. For many years, employees were hired under an opt-in regime with a 0% default. After August 2010, the default changed to auto-enrollment at a 3% contribution rate. This policy change provides a unique opportunity to learn about the mechanisms behind default effects.

We find that present bias and financial literacy both strongly predict retirement saving behavior, but these individual characteristics have different effects under the two default regimes. In an opt-in (i.e. 0% default) regime, one standard deviation higher financial literacy is associated with a one third lower likelihood of being at the default contribution rate, a one fifth higher likelihood of being at the annual maximum, and eight percent higher annual contributions. In contrast, under the auto-enrollment regime, one standard deviation increase in present bias is associated with a one third higher likelihood of being at the default contribution rate (3%), one quarter lower likelihood of being at the annual maximum and nine percent lower annual contributions. In addition, we do not find evidence that present bias is associated with saving decisions in the opt-in regime, nor do we find evidence that financial literacy is associated with saving decisions in the auto-enrollment regime. Our survey was designed to address measurement error by including multiple measures of PB, the long-run discount factor, and EGB. The findings show that the results are robust to using two-stage least squares methods to control for measurement error (Gillen et al., 2017).

We rationalize our results through a conceptual framework based on the model of Carroll et al. (2009), enriched with financial literacy, where the decision to remain at the default depends on the relationship between the default and the individual's optimal saving rate. In an opt-in regime, the important individual-level determinant of selecting the default is financial literacy. Either employees with low financial literacy do not recognize 0% as a poor option, or they cannot understand the alternatives and so they tend to stay at the 0% default. In contrast, neither exponential-growth bias nor procrastination tendencies from PB are related to being at the 0% default in the opt-in regime because even those with PB and EGB are motivated to actively choose a positive contribution level. While 3% is likely to be below optimal for most employees, it is likely closer to many employees' optima. Therefore, when the default improves under auto-enrollment to 3%, a smaller fraction of the population should want to be active. Under the 3% default contribution rate, procrastination becomes the factor that separates individuals who remain passive from those who aim for optimality.

Past research relates measures of financial literacy and PB preferences to retirement wealth accumulation. Much of this prior work considers these explanatory factors one at a time, rather than jointly. It finds that financial literacy affects financial outcomes, including retirement planning (Lusardi and Mitchell, 2007; Hung et al., 2009), which in turn affects retirement savings (Lusardi and Mitchell, 2011; Ameriks et al., 2003). Heutel et al. (2014) find no relationship between PB preferences and whether people have any retirement savings. More recently, Goda et al. (2015) evaluate the relationship between retirement savings, PB preferences, financial literacy, and EGB, finding that each has a distinct and statistically significant relationship with retirement wealth accumulation. Stango, Yoong and Zinman (2017) also find that PB preferences and EGB are among the set of factors that are highly predictive of overall financial condition, which includes retirement wealth. However, none of these papers are well-suited to examine the relationship between these individual characteristics and passive choice in distinct default regimes.

This paper is most closely related to two recent studies that aim to explain saving choices with measures or proxies of present-biased preferences. Using employer administrative data from health and retirement benefits, Brown and Previtero (2014) construct a proxy classification of employees who enrolled in the company health plan on the last possible day as procrastinators. They find that this measure of procrastination is a significant predictor of employees' retirement-plan participation, contribution, and asset allocation decisions. Another related study by Blumenstock, Callen and Ghani (2017) reports on a randomized-controlled trial in Afghanistan measuring the causal effects of employer-provided defaults and matches on short-term savings. Based on data from a follow-up survey that elicits time preferences, present-biased individuals were more likely to remain at the default. However, the institutional context and motivations for saving, namely short-term saving to an interest-free account in Afghanistan, differ greatly from the U.S. context.

Our paper makes several contributions to the existing literature. First, we combine direct elicitations of PB using conventional economic elicitation procedures with administrative data on saving in a U.S. context. This approach extends Brown and Previtero (2014) by addressing a concern that the procrastination proxy could be picking up other contextual or psychological dispositions. For instance, those who find the health plan enrollment confusing may also find the retirement-saving enrollment confusing. In addition, our survey allows us to control for other covariates not present in administrative data that may also affect saving decisions.

Second, we are able to examine the relationship between PB, EGB and financial literacy and saving choices under different default regimes while controlling for other important determinants. We find that the default regime matters and changes who is passive, contrasting with the view that passivity is a fixed characteristic and unrelated to the underlying default (Chetty et al., 2014). Rather than treating "active" and "passive" savers as types, our results suggest that more fundamental economic factors such as time preferences and information interact with the choice environment to produce different levels of passive behavior.

The remainder of this paper is organized as follows. In Section 2, we describe the context and our sources of data, including administrative records and linked survey responses. Section 3 presents the results and Section 4 discusses them. Section 5 concludes.

2 Setting and Data

2.1 Retirement Plan Setting

Benefits-covered federal employees participate in an optional defined contribution (DC) plan, the Thrift Savings Plan (TSP), in addition to a mandatory defined benfit (DB) plan. Employees receive a base TSP contribution of 1 percent from the agency and a further match on employee contributions up to 5 percent of pay. The agency matches each dollar of an employee's first 3 percent of pay and $0.50 on the dollar for next two percent. Employees can contribute up to the IRS maximum each year, which was $18,000 in 2017.[1] Employees may elect to invest their contributions in five different funds or a lifecycle option, which is a mix of the other funds based on the employee's age.

The federal government implemented automatic enrollment for all covered employees hired after August 1, 2010. Before this, employees were required to opt in to participate in TSP. After auto-enrollment started, employees were enrolled in TSP at a 3 percent contribution rate unless they opted out. Therefore, the default contribution rate is zero for those hired prior to August 1, 2010 and 3 percent for those hired later.

Our administrative data combine TSP contribution elections with HR records. These data were collected as of April 2017, and include 5,472 employees. We fielded an online survey between March 29, 2017 to April 14, 2017 to these employees, and 1,585 (29%) provided complete response on the

[1] Employees hired before 1984 are covered by a more comprehensive DB plan and receive no base and no match on employee contributions to TSP, although they are allowed to contribute up to the IRS maximum allowable each year. Fewer than 10 percent of the current full-time, non-seasonal employees are in the more comprehensive plan.

variables of interest. Our survey included one initial invitation and two reminders sent via email. We use this survey to elicit PB preferences, EGB and measures of financial literacy. These 1,585 employees form our analysis sample in this study.

2.2 Outcome variables

We construct each employee's annual TSP contribution amount using data on contribution elections while taking into account the maximum allowable annual contribution of $18,000.[2] We construct additional measures of saving choices including binary indicators of whether the employee passively enrolled, whether the employee's saving choice is consistent with the default in place during their hire date, whether the employee contributes an amount that maximizes their match from the Federal government, whether the employee contributes the annual maximum, and whether the employee contributes to TSP at all. The binary indicator describing whether the employee made a passive choice is only present for employees hired after auto-enrollment (AE) was instituted. This variable differs from whether the employee's saving choice is consistent with the default due to some employees actively electing the default contribution rate.

[2] Employees can elect DC contributions as a percent of pay, or as a dollar amount per pay period.

Table 1: Summary Statistics - Outcome Variables

	Opt-In Regime	Auto-Enroll Regime
TSP Amount ($/year)	8699.480	5160.133
	(6418.502)	(4987.889)
Passive		0.118
		(0.323)
At Default	0.088	0.147
	(0.284)	(0.354)
At Maximum Match	0.614	0.576
	(0.487)	(0.495)
At 0%	0.088	0.048
	(0.284)	(0.215)
At Cap	0.131	0.042
	(0.337)	(0.202)
Observations	735	661

Notes: TSP Amount reflects annual Roth and Traditional TSP contributions subject to annual maximum, including catch-up contributions if eligible. See text for more details.

Table 1 presents summary statistics for our main outcome variables separately for employees who were hired before and after the introduction of automatic enrollment. Because auto-enrollment is determined by hire date, and our data come from a single cross-section, auto-enrollment is confounded with length of service and, to some extent, with age. Employees hired in the opt-in regime have annual TSP contributions of $8,699 on average, while the younger cohort hired under auto-enrollment average $5,160.

Approximately 9 percent of opt-in regime employees are at their default contribution rate of 0 percent, whereas only 4.8 percent of auto-enrolled employees do not participate. Instead, 14.7 percent of auto-enrolled employees are at the default contribution rate of 3 percent. Our data include an indicator of whether the employee made an election or was passively enrolled in the plan. This variable indicates that the vast majority of those at the default contribution rate are there through passive enrollment: 11.8 percent of the sample, or 80 percent of those at the 3-percent default did not actively choose their contribution rate.

The two groups of employees also differ on their contributions at higher levels. Approximately 61 percent of employees hired under the opt-in regime contribute 5 percent of their salary, while 58 percent of auto-enrolled employees contribute 5 percent. Finally, we observe that whereas 13 percent of employees hired under the opt-in regime are contributing the annual maximum of $18,000 per year, only 4.2 percent of auto-enrolled employees are at this cap.

2.3 Present bias

We use a "time-staircase" procedure to construct a simple measure of PB (Beta) as well as of the long-run discount factor (Delta), as in Falk et al. (2014); Goda et al. (2015). The staircases have the form:

Present-Future Staircase: Would you rather receive $100 today or $[$X$] in 12months?

Future-Future Staircase: Would you rather receive $120 in 12 months or $[$Y$] in 24 months?

Subjects begin with a common value of [X] or [Y]. If a subject indicates they prefer the money sooner (later), then the second dollar amount increases (decreases) on the next question.[3] For each staircase, subjects answer five questions, gradually narrowing the interval that contains the indifference point. Since the questions are binary and have parallel structure, they are easily understood and can be answered quickly. Participants were asked these questions for a 12-month (as shown above) and 6-month time interval, for a total of four sets.[4] We randomize the order of the staircases and utilize different base values for the different sets of questions (i.e., the Present-Future Staircase always begins with $100 today and the Future-Future Staircase with $120 in 12 months) to minimize the influence of mechanical responses. While this staircase method did not involve real stakes, Falk et al. (2014) show that behavior between a no-stakes and real-stakes version is highly correlated.[5] From these staircases we construct measures of Beta and Delta from the implied indifference point.[6]

[3] In our survey instrument, the future value X was always greater than 100 and Y was always greater than 120.

[4] We collect multiple measures to address measurement error (see Section 3.2).

[5] The authors find a correlation between the staircase measures and incentivized experimental measures of 0.524.Â This correlation is close to the test-retest correlation of 0.664 for the incentivized experiment.

[6] We cannot identify the indifference point for those who select the upper bound of the time staircase. In this case, we use the upper bound value plus the difference between that value and the second-to-last value to determine the indifference point. We include a dummy variable for those with these imputed values in the analysis.

2.4 Financial literacy

We collect measures of financial literacy in the survey. First, we measure basic financial literacy using the 5-item battery of financial literacy questions developed by Lusardi and Mitchell (2011) and widely used since then (Lusardi and Mitchell, 2014). These questions measure understanding of inflation, diversification, compound interest, mortgage payments, and bond prices using multiple choice questions. OPM employees performed well on these questions relative to the U.S. population; percent correct ranged between 39 and 95 percent for OPM employees, and 21 to 70 percent for a representative sample of the U.S. population (Lusardi and Mitchell, 2011). Similarly, the share of employees who answered all five questions correctly was 30 percent, relative to 10 percent for the U.S. population, suggesting that OPM employees are more financially literate than average. In our subsequent analysis, we use a z-score of financial literacy standardized within the sample.

2.5 Exponential-growth bias

We measure EGB separately given that previous work has found that this bias is particularly important for retirement saving due to its long investment horizon (Stango and Zinman, 2009; Goda et al., 2015). To assess EGB, we include three hypothetical investment questions asking participants to provide a value for an asset given a specified return and time horizon. An example question is, "An asset has an initial value of \$100 and grows at an interest rate of 10% each period. What is the value of the asset after 20 periods?" For each question k and each individual i, we construct a measure of exponential-growth misperception that minimizes the distance between the response and the correct answer Goda et al. (2015). Our measure of Alpha represents the degree of EGB, with Alpha $= 1$ representing no EGB (accurate perception) and Alpha < 1 representing some EGB, where the person underestimates how much assets would be worth under exponential growth. In particular, Alpha $= 0$ represents the perception of growth as linear, rather than exponential. We compute the distance the response is from the correct answer and normalize it by the correct answer. Performance on these questions by OPM employees was similar to the U.S. population: between 29 and 33 percent of survey participants answered the questions within 10% of the correct value as compared to 23 to 31 percent in a representative U.S. sample (Goda et al., 2015).

2.6 Covariates

From HR records, we also have data on pay, basic demographics (gender, birth year, race/ethnicity), human capital (highest education, tenure), and position (non-supervisor, team leader, manager or supervisor) and work location (DC, MD, PA, VA, other). Table 2 presents summary statistics of our measures of Alpha, Beta, Delta, the z-score for financial literacy, and our covariates that are included in all subsequent analyses. The average value of Alpha for the Opt-In sample is 0.52 and for the Auto-Enrollment sample is 0.48, which implies that on average, participants in our sample exhibit EGB. The average Beta of 1 implies that, on average, the sample is time consistent. However, individuals with Beta<1 display PB and those with Beta>1 are future biased, meaning that they over-value the future relative to today in a time inconsistent way. The mean of our sample for Alpha and Beta appear similar to the nationally-representative sample of Goda et al. (2015), while our mean Delta of 0.87 indicates greater patience than in the national population, which had a 0.70 mean. Alpha and financial literacy are standardized within sample. Beta and Delta are not, but instead kept in their theoretically-relevant units.

The two cohorts differ in some notable ways. Their behavioral parameters, financial literacy, ethnic background, and work location are all nearly identical. However, they differ substantially in age and many of the things associated with it. The cohort hired before auto-enrollment is older, is paid more, has higher tenure, has slightly less trust in the federal government, is more likely to be eligible for catch-up contributions, is more educated, and is more likely to be in a supervisory position.

Table 2: Summary Statistics - Survey Measures and Controls

	Opt-In Regime		Auto-Enroll Regime		Difference	
	mean	sd	mean	sd	b	p
Alpha	0.52	0.85	0.48	0.75	0.05	(0.28)
Beta	1.01	0.09	1.00	0.09	0.00	(0.50)
Delta	0.87	0.09	0.87	0.09	0.01	(0.19)
Total Pay	98456.47	26404.52	73073.82	32918.61	25382.65***	(0.00)
Age	50.87	9.82	43.37	10.52	7.51***	(0.00)
Tenure in Years	14.01	7.41	2.94	2.22	11.08***	(0.00)
Trust in Fed. Gov. as Employer	3.19	1.06	3.31	1.01	-0.12*	(0.03)
Fin Lit (z-score)	-0.07	1.04	0.00	0.95	-0.07	(0.16)
Eligible for Catch-Up Contributions	0.61	0.49	0.29	0.46	0.31***	(0.00)
Highest Education						
High School	0.18	0.38	0.15	0.36	0.02	(0.25)
College	0.19	0.39	0.14	0.34	0.05*	(0.01)
Bachelor	0.44	0.50	0.35	0.48	0.09***	(0.00)
Post Bachelor	0.20	0.40	0.36	0.48	-0.16***	(0.00)
Race/Ethnicity:						
White	0.71	0.45	0.72	0.45	-0.01	(0.69)
Hispanic	0.04	0.20	0.05	0.21	-0.00	(0.76)
Black	0.20	0.40	0.19	0.39	0.01	(0.66)
Other Race	0.05	0.21	0.04	0.20	0.00	(0.74)
Work Location:						
DC	0.26	0.44	0.26	0.44	-0.01	(0.70)
MD	0.10	0.30	0.08	0.28	0.02	(0.26)
PA	0.28	0.45	0.31	0.46	-0.03	(0.27)
VA	0.04	0.20	0.05	0.22	-0.01	(0.42)
Other Location	0.32	0.47	0.30	0.46	0.03	(0.27)
Job Position:						
Non-Supervisory	0.81	0.39	0.93	0.25	-0.12***	(0.00)
Team Leader	0.04	0.21	0.02	0.13	0.03**	(0.00)
Supervisor or Manager	0.14	0.35	0.05	0.21	0.10***	(0.00)
Observations	735		661		1396	

Notes: Trust in Fed. Gov. as Employer reflects level of agreement with the following statement: "Benefits by Fed. Gov. are designed to best fit the needs of its employees."

Fin Lit reflects number of correct answers among Big Five financial literacy questions.

3 Results

3.1 Main Results

We analyze the relationship between survey-based measures of Alpha, Beta, Delta and financial literacy and contribution choices separately by enrollment regime. We test whether the measured parameters have different effects on savings outcomes based on whether employees had to opt-in or would have been auto-enrolled at the time of hire.

The first set of outcomes in Table 3 considers the role of PB, EGB and financial literacy on the likelihood of contributing the default rate. For employees hired in the opt-in regime, this variable represents whether the employee is still at a zero percent contribution rate. For those hired in the auto-enrollment regime, it represents whether the employee is at a 3 percent contribution rate and includes both those who were passively defaulted into the 3 percent contribution rate and those who actively selected it. Due to the possibility that these different default contribution rates have different potential for "stickiness" due to procrastination, we conduct our analysis separately on those hired under the two regimes. The results show no evidence that Beta is a predictor of remaining at the default when the default contribution rate is zero in Column (1), but strong evidence that lower levels of Beta (i.e. more procrastination tendencies) are associated with a higher likelihood of remaining at the default when the default contribution rate is 3 percent in Column (2). The coefficient on Beta of -0.554 in Column (2) of Table 3 implies that a one standard deviation decrease in Beta is associated with a 5.0 percentage point (34 percent) higher probability of being at the default. This coefficient is statistically distinguishable from the coefficient on Beta in Column (1) with $p<0.01$ indicating that present bias has a significantly larger effect in the auto-enrollment regime than the opt-in regime.

The outcome in Column (3) of Table 3 represents whether employees were passively enrolled into the TSP. Because this outcome variable is only available for those hired in the auto-enrollment regime, we focus on this subsample, as indicated in a row below the regression results. Failing to make an active choice is strongly correlated with Beta, but we find no evidence that it is correlated with Alpha, Delta, or financial literacy. The coefficient of -0.401 on Beta implies that a one standard deviation decrease in Beta, corresponding to more present bias, is associated with a 3.6 percentage point higher probability of passive behavior. The magnitude is economically significant, representing a 31 percent change relative to the mean.

In Columns (4) and (5) we examine the probability of being at 0% contributions under the two regimes.[7] The unconditional probability of being at 0% before auto-enrollment (0.088) is larger than the probability after auto-enrollment (0.048) with $p<0.01$. This difference exists despite the before auto-enrollment cohort having higher tenure, being older, and being better educated, and is a testament to the power of defaults. Here, we find that the coefficient on financial literacy is statistically significant in Column (4). The coefficient of -0.027 represents a 31 percent decrease in the probability of being at the default from a standard deviation increase of financial literacy. By contrast, the coefficient on financial literacy is not statistically significant in Column (5), and is statistically different from the coefficient in Column (4) ($p=0.044$). Therefore, our results suggest that higher financial literacy reduces non-participation more in the opt-in regime relative to the auto-enrollment regime.

[7] Note Column (4) is a replica of Column (1) because the default equals 0% before auto-enrollment.

Table 3: Relationship between Alpha, Beta and Delta with TSP Outcomes (Default, Passive, 0%) - OLS Prediction

	(1) At Default	(2) At Default	(3) Passive	(4) At 0%	(5) At 0%
Alpha	-0.012	-0.021	-0.003	-0.012	0.016
	(0.012)	(0.018)	(0.016)	(0.012)	(0.015)
Beta	0.199	-0.554***	-0.394**	0.199	-0.113
	(0.145)	(0.193)	(0.174)	(0.145)	(0.124)
Delta	0.054	-0.118	-0.085	0.054	-0.008
	(0.130)	(0.176)	(0.163)	(0.130)	(0.121)
Fin Lit (z-score)	-0.027**	-0.007	-0.007	-0.027**	0.006
	(0.013)	(0.016)	(0.014)	(0.013)	(0.010)
College or Associate	0.023	-0.033	-0.107**	0.023	0.005
	(0.047)	(0.055)	(0.051)	(0.047)	(0.041)
Bachelor	-0.076*	0.012	-0.037	-0.076*	-0.049
	(0.039)	(0.049)	(0.048)	(0.039)	(0.031)
Post-Bachelor	-0.104**	-0.012	-0.051	-0.104**	-0.041
	(0.043)	(0.050)	(0.048)	(0.043)	(0.035)
White	0.043	-0.023	0.060**	0.043	-0.004
	(0.034)	(0.062)	(0.025)	(0.034)	(0.036)
Hispanic	0.044	-0.005	0.119**	0.044	-0.002
	(0.054)	(0.082)	(0.060)	(0.054)	(0.049)
Black	0.096**	0.016	0.122***	0.096**	0.072
	(0.042)	(0.068)	(0.035)	(0.042)	(0.046)
Eligible for Catch-Up Contributions	-0.047	-0.023	-0.025	-0.047	-0.029
	(0.040)	(0.052)	(0.050)	(0.040)	(0.040)
Constant	-0.099	1.467***	1.070***	-0.099	0.448
	(0.315)	(0.403)	(0.385)	(0.315)	(0.280)
Alpha	OLS	OLS	OLS	OLS	OLS
Beta	OLS	OLS	OLS	OLS	OLS
Delta	OLS	OLS	OLS	OLS	OLS
Sample	Opt-In Regime	Auto-Enroll Regime	Auto-Enroll Regime	Opt-In Regime	Auto-Enroll Regime
Mean DV	.088	.147	.118	.088	.048
R-squared	0.081	0.098	0.113	0.081	0.043
Cluster	735	661	651	735	661
Observations	735	661	651	735	661

Notes: Standard errors in parentheses and clustered on ID. Dependent variable in column heading.

All specifications also include controls for for pay, pay squared, age, age squared, years of tenure, years of tenure squared, Work Location, Job Position and Trust in Fed. Gov. as Employer.

* p < 0.10, ** p < 0.05, *** p < 0.01.

In Table 4 we report results similar to Table 3 but for annual TSP contributions, an indicator for receiving the maximum match, and an indicator for being at the annual maximum. Column (1) shows that there is no statistically significant effect of Alpha or Beta in the opt-in regime, but the coefficient financial literacy is statistically significant. A standard deviation increase in financial literacy is associated with a $684 or 8 percent increase in annual contributions under the opt-in regime. In the auto-enrollment regime, higher Beta (lower PB) is associated with higher contributions. A one standard deviation decrease in Beta is associated with $473 or a 9 percent decrease in annual contributions. As we saw in TSP participation in Table 3, the coefficients on financial literacy are statistically different from one another (p=0.21), indicating that financial literacy has a stronger effect on contributions in the opt-in regime. Consistent with theory, the long run discount factor Delta is associated with higher annual contributions in both regimes.

Columns (3) and (4) in Table 4 examines whether our measures predict which employees maximize the employer match by contributing at least 5 percent of salary. Strangely, we find that Beta is negatively associated with maximizing the match under the opt-in regime.[8] Neither Alpha, Delta, nor financial literacy predict maximizing the match.

Finally, we examine the relationship between our measures and contributing the $18,000 per year maximum annual contribution. Column (5) shows that in the opt-in regime, one standard deviation higher financial literacy increases the probability of capping out total contributions by 2.9 percentage points or 20 percent. Alpha and Beta are not significant predictors. In the auto-enrollment regime, a standard deviation decrease in Beta is associated 1.5 percentage point or a 26 percent increase in being at the cap. Neither Alpha nor financial literacy are statistically significant and the coefficients on financial literacy are statistically different across the two regimes.

[8] Later, in the robustness section, we control for measurement error and find that the coefficient is no longer significant.

Table 4: Relationship between Alpha, Beta and Delta with TSP Outcomes (Amount, Max Match, Cap) - OLS Prediction

	(1) TSP Amt.	(2) TSP Amt.	(3) At Maximum Match	(4) At Maximum Match	(5) At Cap	(6) At Cap
Alpha	268.808	146.018	0.002	-0.002	-0.001	0.004
	(241.668)	(197.238)	(0.021)	(0.027)	(0.013)	(0.008)
Beta	3230.082	5259.325***	-0.498**	0.079	0.208	0.136*
	(2782.962)	(1626.511)	(0.228)	(0.244)	(0.141)	(0.070)
Delta	5651.808**	3947.988**	0.082	-0.353	0.231	0.211**
	(2601.748)	(1627.919)	(0.226)	(0.234)	(0.145)	(0.083)
Fin Lit (z-score)	684.246***	56.760	0.002	-0.022	0.025**	0.001
	(233.851)	(146.118)	(0.018)	(0.021)	(0.012)	(0.008)
College or Associate	-346.038	495.929	0.008	-0.031	-0.046	0.016
	(688.143)	(490.066)	(0.062)	(0.073)	(0.032)	(0.021)
Bachelor	1914.170***	648.250*	0.091	0.035	0.026	-0.005
	(657.006)	(361.465)	(0.056)	(0.062)	(0.034)	(0.011)
Post-Bachelor	2973.074***	770.858*	0.099	0.009	0.032	0.024
	(823.067)	(446.349)	(0.067)	(0.066)	(0.044)	(0.015)
White	-367.384	-1730.337*	0.086	0.018	-0.089	0.023
	(1110.246)	(971.478)	(0.085)	(0.099)	(0.074)	(0.046)
Hispanic	-1504.723	-1132.797	0.077	-0.159	-0.221***	0.017
	(1381.673)	(1253.959)	(0.123)	(0.132)	(0.077)	(0.065)
Black	-2762.674**	-3111.365***	0.004	-0.161	-0.173**	0.012
	(1202.453)	(1027.179)	(0.094)	(0.104)	(0.078)	(0.046)
Eligible for Catch-Up Contributions	2636.404***	-295.854	0.019	0.048	0.076*	0.014
	(765.710)	(616.323)	(0.067)	(0.080)	(0.046)	(0.032)
Constant	-15142.492**	-6828.587*	1.609***	-0.294	-0.999***	-0.501***
	(6549.674)	(3561.770)	(0.587)	(0.516)	(0.364)	(0.180)
Alpha	OLS	OLS	OLS	OLS	OLS	OLS
Beta	OLS	OLS	OLS	OLS	OLS	OLS
Delta	OLS	OLS	OLS	OLS	OLS	OLS
Sample	Opt-In Regime	Auto-Enroll Regime	Opt-In Regime	Auto-Enroll Regime	Opt-In Regime	Auto-Enroll Regime
Mean DV	8699.48	5160.133	.614	.576	.131	.042
R-squared	0.282	0.450	0.086	0.073	0.139	0.134
Cluster	735	661	735	661	735	661
Observations	735	661	735	661	735	661

Notes: Standard errors in parentheses and clustered on ID. Dependent variable in column heading.

All specifications also include controls for for pay, pay squared, age, age squared, years of tenure, years of tenure squared, Work Location, Job Position and Trust in Fed. Gov. as Employer.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.2 Robustness

Unlike the administrative outcomes, there is reason to believe that our survey measures are subject to measurement error. Including multiple elicitations in our survey, however, provides us with two possible strategies for overcoming this.

The first strategy is simply to average the multiple measures and conduct OLS analysis using the mean value as a regressor, which we do in our main results. Under the assumption that our multiple measures of each characteristic are in fact noisy measures of a "true" characteristic and that the errors in the multiple measures are uncorrelated, then it follows trivially that the level of measurement error will be reduced but not eliminated by taking the means. As a result, using a mean value should yield less-biased results in OLS than using a single measure.

This OLS approach is not, however, the most efficient way of using our data. The second approach follows the "Obviously Related Instrumental Variables" (ORIV) approach of Gillen, Snowberg and Yariv (2017). A standard approach to dealing with a variable measured with noise is the use of an instrument uncorrelated with that noise. A second survey measure, provided the measurement error is uncorrelated, can provide such an instrument. However, experimenters often lack a theory for which survey measure should be the regressor and which the instrument. The ORIV solution is to use all measures simultaneously as regressors and as instruments for one another. That is, the true model is given by $Y = \alpha + \gamma X^*$, but the econometrician only has noisy measures $X^i = X^* + \nu_i$ for $i = 1, 2$ with ν_1 and ν_2 uncorrelated. One estimates the model:

$$\begin{pmatrix} Y \\ Y \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \gamma \begin{pmatrix} X^1 \\ X^2 \end{pmatrix}, \text{ instrumenting } \begin{pmatrix} X^1 \\ X^2 \end{pmatrix} \text{ with } W = \begin{pmatrix} X^2 & 0 \\ 0 & X^1 \end{pmatrix}$$

Gillen, Snowberg and Yariv (2017) prove that ORIV produces consistent estimates of γ (Proposition 1), and that the estimated standard errors, when clustered by subject, are consistent estimates of the asymptotic standard errors (Proposition 2).

While we can adapt this two-measure approach to our multiple-measure, multiple-outcome setting straightforwardly, the method places stronger demands on the relationships between the multiple measures. We therefore first determine for which parameters the ORIV approach is appropriate to allow us to utilize our data in a more efficient manner than the OLS approach.

Table 5: Fitting TSP Contributions with OLS and IV specifications of Alpha, Beta and Delta

	(1) TSP Amt.	(2) TSP Amt.	(3) TSP Amt.	(4) TSP Amt.	(5) TSP Amt.	(6) TSP Amt.	(7) TSP Amt.	(8) TSP Amt.
Alpha	247.99	383.04	228.39	240.52	344.05	374.58	14.70	354.22
	(162.20)	(237.03)	(165.95)	(160.37)	(244.14)	(236.17)	(1113.33)	(242.61)
Beta	4169.78**	3988.22**	-13500.17*	6774.12***	-12945.72*	6288.68***	-101888.21	-10492.38**
	(1622.39)	(1657.60)	(7059.51)	(2143.83)	(7181.24)	(2175.67)	(490832.31)	(4370.03)
Delta	5080.06***	4590.10***	-2846.29	10311.01***	-2933.93	9211.26***	2836.46	-3026.31
	(1551.27)	(1570.74)	(3483.58)	(3274.88)	(3526.69)	(3279.17)	(17966.08)	(3422.97)
Fin Lit (z-score)	411.17***	424.60***	469.96***	403.07***	512.58***	415.79***	770.25	498.80***
	(147.23)	(151.67)	(151.88)	(147.45)	(158.49)	(153.30)	(1677.88)	(154.48)
Total Pay	0.10***	0.10***	0.10***	0.10***	0.10***	0.10***	0.15	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.22)	(0.02)
Total Pay × Total Pay	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	49.07	66.79	9.18	60.29	27.33	76.93	-130.75	31.47
	(91.22)	(93.26)	(95.06)	(91.52)	(97.53)	(94.35)	(856.82)	(95.83)
Age × Age	-0.62	-0.85	-0.31	-0.71	-0.55	-0.93	0.80	-0.58
	(1.05)	(1.07)	(1.08)	(1.05)	(1.11)	(1.08)	(6.84)	(1.09)
College or Associate	233.16	188.51	416.58	100.54	357.44	77.24	156.00	361.98
	(428.38)	(437.39)	(436.43)	(434.18)	(446.70)	(445.87)	(1010.29)	(442.84)
Bachelor	1563.17***	1572.43***	1664.03***	1454.31***	1628.60***	1476.97***	1119.78	1649.32***
	(385.42)	(392.68)	(396.57)	(388.46)	(405.47)	(398.91)	(2099.40)	(403.23)
Post-Bachelor	1918.61***	1945.99***	2066.19***	1790.94***	2052.80***	1833.86***	1622.57	2069.40***
	(462.22)	(470.68)	(477.38)	(465.82)	(487.26)	(478.14)	(1496.47)	(485.16)
White	-1028.36	-954.96	-1090.40	-1056.82	-1001.92	-986.50	-1820.30	-982.66
	(740.71)	(735.89)	(762.61)	(735.20)	(762.12)	(737.21)	(3803.60)	(757.99)
Hispanic	-1416.64	-1293.59	-1236.25	-1480.25	-1107.64	-1356.79	-746.97	-1122.12
	(938.97)	(927.95)	(975.39)	(929.06)	(971.79)	(926.60)	(3724.87)	(961.94)
Black	-2999.71***	-2856.97***	-3225.14***	-2991.14***	-3004.70***	-2861.10***	-4627.77	-2975.35***
	(787.21)	(785.71)	(810.61)	(781.74)	(814.99)	(787.32)	(7653.03)	(808.81)
Tenure in Years	173.20***	173.98***	172.58***	169.06***	174.76***	170.31***	122.30	175.82***
	(60.96)	(62.05)	(63.05)	(60.39)	(64.44)	(62.04)	(258.06)	(63.94)
Tenure in Years × Tenure in Years	-4.38***	-4.46**	-3.98**	-4.35***	-4.06**	-4.45**	-1.07	-4.14**
	(1.69)	(1.75)	(1.76)	(1.68)	(1.82)	(1.75)	(15.57)	(1.80)
Eligible for Catch-Up Contributions	1665.48***	1709.26***	2002.93***	1590.71***	2040.19***	1644.86***	3411.50	1998.63***
	(497.41)	(504.49)	(539.93)	(495.97)	(551.10)	(506.97)	(8316.09)	(531.79)
Constant	-11254.46***	-10960.96***	13921.57	-18463.17***	13154.40	-17315.75***	100824.77	10672.15
	(3480.26)	(3535.51)	(10213.13)	(5292.42)	(10392.85)	(5325.65)	(523921.66)	(7208.36)
Alpha	OLS	IV	OLS	OLS	IV	IV	OLS	IV
Beta	OLS	OLS	IV	OLS	IV	OLS	IV	IV
Delta	OLS	OLS	OLS	IV	OLS	IV	IV	IV
F-Stat Alpha		521.51			261.54	267.19		179.80
F-Stat Beta			11.88		5.60		0.23	79.11
F-Stat Delta				101		50	262	253
Mean DV	7023.61	7031.85	7023.61	7023.61	7031.85	7031.85	7023.61	7031.85
R-squared	.371	.362	.285	.357	.283	.351	.	.306
Cluster	1396	1343	1396	1396	1343	1343	1396	1343
Observations	1396	4029	2792	2792	8058	8058	2792	16116

Notes: Standard errors in parentheses and clustered on ID. Dependent variables as indicated in column heading.

All specifications also include controls for pay, pay squared, age, age squared, years of tenure, years of tenure squared, Work Location, Job Position and Trust in Fed. Gov. as Employer.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5, we regress TSP contribution levels on our survey measures and other controls, considering all possible permutations of OLS and ORIV for Alpha, Beta, and Delta. The outcome in all eight columns is annual TSP contributions in dollars, as of April 2017. Column (1) is the most straightforward to interpret, being an OLS regression using the mean values of Alpha, Beta, and Delta as well as the standard controls. Both Beta and Delta are strongly related to TSP contributions, with estimated coefficients of $4,170 and $5,080 and significant at the 5 and 1 percent levels, respectively. This implies a one standard deviation increase in Beta is associated with $375 higher annual contributions, and a one standard deviation increase in Delta is associated with $457 higher annual contributions. These results are comparable to the $411 increase associated with a one standard deviation increase in our measure of general financial literacy, which is significant at the 1 percent level. The coefficient on Alpha is somewhat smaller at $248 and is also not statistically significant.

The remaining columns of Table 5 attempt to use the ORIV strategy, first for one measure at a time, then two, then all three in Column (8). Which measures are instrumented are indicated in the rows immediately below the coefficient estimates. When only Alpha is instrumented in Column (2), the coefficient increases from $248 to $383, but remains just shy of statistical significance at conventional levels. Delta is instrumented in Column (4), which doubles its estimated coefficient to $10,311 and it remains highly statistically significant. Unusually, when Beta is instrumented in Column (3), the coefficient becomes large and changes sign, becoming marginally significant at -$13,500. This occurs because our two Beta measures are not strong predictors of one another. Whereas the multiple Alpha measures are all correlated with each other with correlations above 0.4, and the two Delta measures correlated at 0.45, our two Beta measures are correlated only at 0.09 (a full correlation matrix is available in Appendix A). Attempting ORIV for Beta thus results in a weak instruments problem, suggesting that the technique is not appropriate for that measure.

Given that ORIV is not appropriate for Beta, the full ORIV approach shown in Column (8) is also not appropriate. Instead, the next best approach, and our preferred specification, is to use ORIV for Alpha and Delta, and simply use the arithmetic mean of Beta. This is shown in Column (6) of Table 5. The results are reassuringly similar to the preceding columns. The coefficient on Alpha remains economically meaningful at $375 and not quite statistically significant. The coefficients on Beta and Delta are both large, at $6,289 and $9,211, respectively, and both significant at the 1 percent level. It is also worth noting that the coefficient on the general financial literacy score remains large and highly significant at $416.[9]

We replicate Tables 3 and 4 using ORIV with the preferred specification from Column (6) of Table 5, instrumenting for Alpha and Delta and averaging our two measures of Beta. Comparing Tables 3 and 4 to Tables 6 and 7, the coefficients are slightly larger in magnitude using ORIV, but the main implications are the same. Financial literacy is statistically significant in predicting default enrollment, non-participation and annual contributions under the opt-in regime and Beta is statistically significant in predicting passive choice, being at the default, annual TSP contributions and contributing the annual maximum under auto-enrollment. The one coefficient that is no longer significant is the effect of Beta on maximum match under opt-in. In Table 4 the coefficient was significant and negative, surprisingly implying that more patience leads to less use of the maximum match. Once we correct for measurement error, this association disappears, suggesting lack of robustness.

[9]We provide first-stage results for the specifications in Column (6) and Column (8) in Appendix A.

Table 6: Relationship between Alpha, Beta and Delta with TSP Outcomes (Default, Passive, 0%) - OLS/IV Prediction

	(1) At Default	(2) At Default	(3) Passive	(4) At 0%	(5) At 0%
Alpha	-0.022	-0.030	-0.002	-0.022	0.021
	(0.016)	(0.027)	(0.025)	(0.016)	(0.023)
Beta	0.256	-0.622**	-0.481**	0.256	-0.110
	(0.189)	(0.247)	(0.229)	(0.189)	(0.166)
Delta	0.245	-0.235	-0.182	0.245	-0.008
	(0.257)	(0.361)	(0.342)	(0.257)	(0.251)
Fin Lit (z-score)	-0.028**	-0.012	-0.012	-0.028**	0.007
	(0.014)	(0.016)	(0.014)	(0.014)	(0.010)
Total Pay	-0.000	-0.000***	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Pay × Total Pay	0.000	0.000***	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.002	-0.012	-0.006	-0.002	-0.011
	(0.009)	(0.011)	(0.010)	(0.009)	(0.008)
Age × Age	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
College or Associate	0.011	-0.022	-0.099*	0.011	0.003
	(0.047)	(0.056)	(0.052)	(0.047)	(0.044)
Bachelor	-0.090**	0.000	-0.041	-0.090**	-0.049
	(0.039)	(0.050)	(0.048)	(0.039)	(0.032)
Post-Bachelor	-0.115***	-0.022	-0.062	-0.115***	-0.048
	(0.043)	(0.051)	(0.048)	(0.043)	(0.035)
White	0.038	-0.025	0.062**	0.038	-0.010
	(0.034)	(0.061)	(0.025)	(0.034)	(0.035)
Hispanic	0.040	-0.003	0.122**	0.040	-0.004
	(0.053)	(0.081)	(0.060)	(0.053)	(0.049)
Black	0.088**	0.003	0.109***	0.088**	0.067
	(0.041)	(0.068)	(0.036)	(0.041)	(0.045)
Tenure in Years	0.003	-0.045*	-0.047*	0.003	0.014
	(0.007)	(0.027)	(0.025)	(0.007)	(0.017)
Tenure in Years × Tenure in Years	-0.000	0.005	0.005	-0.000	-0.002
	(0.000)	(0.004)	(0.004)	(0.000)	(0.002)
Eligible for Catch-Up Contributions	-0.040	-0.042	-0.040	-0.040	-0.022
	(0.039)	(0.052)	(0.049)	(0.039)	(0.042)
Constant	-0.357	1.597***	1.201**	-0.357	0.477
	(0.447)	(0.582)	(0.556)	(0.447)	(0.404)
Alpha	IV	IV	IV	IV	IV
Beta	OLS	OLS	OLS	OLS	OLS
Delta	IV	IV	IV	IV	IV
F-Stat Alpha	177.386	88.049	93.108	177.386	88.049
F-Stat Delta	25.811	21.581	20.329	25.811	21.581
Sample	Opt-In Regime	Auto-Enroll Regime	Auto-Enroll Regime	Opt-In Regime	Auto-Enroll Regime
Mean DV	.087	.143	.116	.087	.047
R-squared	.071	.089	.11	.071	.042
Cluster	705	638	629	705	638
Observations	4230	3828	3774	4230	3828

Notes: Standard errors in parentheses and clustered on ID. Dependent variable in column heading.

All specifications also include controls for for pay, pay squared, age, age squared, years of tenure, years of tenure squared, Work Location, Job Position and Trust in Fed. Gov. as Employer.

Table 7: Relationship between Alpha, Beta and Delta with TSP Outcomes (Amount, Max Match, Cap) - OLS/IV Prediction

	(1) TSP Amt.	(2) TSP Amt.	(3) At Maximum Match	(4) At Maximum Match	(5) At Cap	(6) At Cap
Alpha	343.284	285.815	0.009	-0.014	-0.008	0.009
	(335.707)	(311.523)	(0.029)	(0.041)	(0.018)	(0.013)
Beta	5401.092	7091.528***	-0.446	-0.137	0.289	0.230**
	(3809.223)	(2126.547)	(0.310)	(0.316)	(0.200)	(0.102)
Delta	9347.045*	7962.024**	0.115	-0.738	0.408	0.419**
	(5482.675)	(3492.184)	(0.457)	(0.488)	(0.302)	(0.179)
Fin Lit (z-score)	711.376***	66.282	-0.001	-0.022	0.031***	0.003
	(245.291)	(150.289)	(0.019)	(0.022)	(0.012)	(0.008)
Total Pay	0.133***	0.097***	0.000	0.000***	0.000	-0.000
	(0.041)	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)
Total Pay × Total Pay	-0.000	-0.000	-0.000*	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	213.134	-138.720	-0.025	0.028*	0.026**	0.009**
	(187.929)	(115.421)	(0.017)	(0.015)	(0.010)	(0.004)
Age × Age	-2.632	2.123	0.000	-0.000*	-0.000***	-0.000**
	(1.882)	(1.409)	(0.000)	(0.000)	(0.000)	(0.000)
College or Associate	-484.224	347.856	0.013	-0.025	-0.052	0.011
	(699.077)	(512.542)	(0.063)	(0.075)	(0.033)	(0.022)
Bachelor	1876.846***	528.298	0.098*	0.048	0.017	-0.009
	(666.012)	(370.810)	(0.057)	(0.063)	(0.034)	(0.012)
Post-Bachelor	2943.631***	675.983	0.104	0.029	0.030	0.017
	(837.330)	(462.971)	(0.068)	(0.066)	(0.045)	(0.016)
White	-279.625	-1690.547*	0.105	0.026	-0.104	0.022
	(1100.874)	(948.469)	(0.085)	(0.098)	(0.074)	(0.045)
Hispanic	-1252.954	-1205.111	0.097	-0.143	-0.225***	0.010
	(1351.611)	(1218.177)	(0.122)	(0.132)	(0.078)	(0.064)
Black	-2632.060**	-2914.950***	0.000	-0.150	-0.176**	0.017
	(1202.146)	(1011.776)	(0.094)	(0.104)	(0.079)	(0.045)
Tenure in Years	117.036	-555.419*	-0.002	-0.031	0.012	-0.001
	(144.423)	(329.528)	(0.013)	(0.037)	(0.008)	(0.016)
Tenure in Years × Tenure in Years	-3.197	79.559*	0.000	0.004	-0.000	0.000
	(3.390)	(45.794)	(0.000)	(0.005)	(0.000)	(0.002)
Eligible for Catch-Up Contributions	2664.957***	-423.779	0.006	0.065	0.076*	0.011
	(769.239)	(629.512)	(0.068)	(0.081)	(0.045)	(0.032)
Constant	-21228.085**	-12050.435**	1.444*	0.280	-1.240**	-0.768***
	(9768.784)	(5336.633)	(0.838)	(0.767)	(0.543)	(0.279)
Alpha	IV	IV	IV	IV	IV	IV
Beta	OLS	OLS	OLS	OLS	OLS	OLS
Delta	IV	IV	IV	IV	IV	IV
F-Stat Alpha	177.386	88.049	177.386	88.049	177.386	88.049
F-Stat Delta	25.811	21.581	25.811	21.581	25.811	21.581
Sample	Opt-In Regime	Auto-Enroll Regime	Opt-In Regime	Auto-Enroll Regime	Opt-In Regime	Auto-Enroll Regime
Mean DV	8685.865	5204.147	.613	.58	.129	.042
R-squared	.26	.438	.086	.06	.131	.11
Cluster	705	638	705	638	705	638
Observations	4230	3828	4230	3828	4230	3828

Notes: Standard errors in parentheses and clustered on ID. Dependent variable in column heading.

All specifications also include controls for for pay, pay squared, age, age squared, years of tenure, years of tenure squared, Work Location, Job Position and Trust in Fed. Gov. as Employer.

* p < 0.10, ** p < 0.05, *** p < 0.01.

4 Discussion

Carroll et al. (2009) provide a useful framework for thinking about defaults in the context of our results. In their model, employees face a fixed cost to making an active decision. This fixed cost is immediate while the benefits are in the future, hence a present-biased employee has motivation to procrastinate active choice. The closer the default is to the optimal saving rate, the greater the procrastination will be. This story can partially rationalize our findings. When the default contribution rate is 0%, the default is so undesirable that even procrastinators will be motivated to make a change. Or, to state this more generally, present bias is not an important factor that affects active choice in an opt-in enrollment regime. When the default is raised to 3% under auto-enrollment, present bias becomes a relevant individual characteristic that separates those who are willing to go the extra length for optimal savings versus those who are satisfied that 3% is "good enough".[10]

Our findings suggest that this narrative ought to be supplemented with financial literacy. Those who are financially illiterate are more likely to have no clear understanding of what a good saving rate is, or may be completely unaware that there is a choice to be made. It may take this fairly severe level of non-understanding to remain at such an undesirable default of 0%. In contrast, when the default is mediocre at 3%, procrastination becomes the dominant driver of passive choice. Moreover, even highly financially illiterate employees will be more likely to notice the 3% deduction coming out of their paycheck and take some action.

5 Conclusion

This paper directly assesses potential mechanisms for explaining observed saving choices in the context of a large U.S. employer's retirement savings plan. In particular, we examine the role that present bias, financial literacy, and exponential-growth bias have in explaining whether employees make active saving choices, respond to match incentives and take full advantage of tax-preferred saving vehicles.

The results show that present bias appears to play an important role under auto-enrollment

[10] This is an interpretation of the results in the context of the theory and not an a priori prediction of the theory. Depending on the parameters of the model, it is possible to get the exact opposite prediction. Nonetheless, the theory provides a useful way to think about the processes that are generating the data.

whereas financial literacy plays a more important role under an opt-in regime. Under auto-enrollment, more present bias (i.e. lower Beta), is associated with a higher likelihood of remaining at the default, lower contributions, and a lower probability of being at the annual cap. Under the opt-in regime, higher financial literacy is associated with a lower likelihood of remaining at the default, higher contributions, and a higher probability of being at the annual cap.

Our findings suggest that both present bias and financial illiteracy are potential mechanisms for the "default effect," which has been shown to be prevalent in a variety of different contexts to be important in retirement savings plans. However, the precise mechanism appears to differ based on what the underlying default is. In particular, we find present bias to be an important mechanism for staying at the default in auto-enrollment regimes, while financial literacy appears to be a more important predictor in opt-in default environments. These results suggest that the characteristics of those who follow the default are not fixed but differ based on the underlying default and that how the default is set can have distributional implications. For instance, a causal interpretation of our results suggests that auto-enrollment increases saving primarily among those with financial literacy.

We caution care when directly applying these results to other employment situations. The sample is particularly well educated and with commensurately high pay. In addition the employer is the Federal Government which constitutes a work environment that may differ in important ways from work environments in the private sector, such as different lengths of tenure and separation probabilities. That said, our findings suggest that developing ways to mitigate present bias and improve financial literacy may change saving outcomes and ultimately improve welfare. Importantly, our results suggest that interventions may need to vary based on terms of the default. Identifying potential interventions remains an important area for future research.

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Appendix A Additional Tables

Table A.1: First Stage for Column (6), Table 1

	(1)	(2)
	Alpha	Delta
IV Alpha 1	0.307***	0.000
	(0.013)	(0.001)
IV Alpha 2	0.307***	0.000
	(0.013)	(0.001)
IV Delta	0.032	0.333***
	(0.072)	(0.033)
IV Beta	-0.075	-0.333***
	(0.119)	(0.019)
Mean DV	.505	.871
R-squared	0.290	0.266
Cluster	1343	1370
Observations	16116	16224

Notes: Standard errors in parentheses and clustered on ID. Dependent variable in column heading. Controls include: Total Pay Squared, Age Squared, Tenure Squared, Fin Lit (z-score), Education, Race, Job Location, Trust in Fed. Gov as Employer, Catch-Up Eligibility.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: First Stage for Column (8), Table 1

	(1)	(2)	(3)
	Alpha	Beta	Delta
IV Alpha 1	0.308***	-0.001	0.001
	(0.013)	(0.001)	(0.001)
IV Alpha 2	0.308***	-0.001	0.000
	(0.013)	(0.001)	(0.001)
IV Beta	-0.034	-0.097**	-0.150***
	(0.054)	(0.039)	(0.008)
IV Delta	0.045	-0.352***	0.392***
	(0.068)	(0.023)	(0.031)
Mean DV	.505	1.006	.871
R-squared	0.290	0.096	0.233
Cluster	1343	1370	1370
Observations	16116	16224	16224

Notes: Standard errors in parentheses and clustered on ID. Dependent variable in column heading. Controls include: Total Pay Squared, Age Squared, Tenure Squared, Fin Lit (z-score), Education, Race, Job Location, Trust in Fed. Gov as Employer, Catch-Up Eligibility.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Correlation Matrix

	Mean Alpha	Alpha 1	Alpha 2	Alpha 3	Mean Beta	Beta 1	Beta 2	Mean Delta	Delta 1	Delta 2
Mean Alpha	1.000									
Alpha 1	0.826***	1.000								
Alpha 2	0.822***	0.540***	1.000							
Alpha 3	0.773***	0.416***	0.444***	1.000						
Mean Beta	-0.004	-0.005	-0.012	0.005	1.000					
Beta 1	-0.018	-0.012	-0.028	-0.008	0.865***	1.000				
Beta 2	0.020	0.009	0.022	0.023	0.576***	0.087***	1.000			
Mean Delta	0.035	0.032	-0.001	0.051*	-0.466***	-0.438***	-0.211***	1.000		
Delta 1	0.017	0.016	-0.007	0.036	-0.495***	-0.624***	0.033	0.870***	1.000	
Delta 2	0.045	0.040	0.005	0.052*	-0.286***	-0.091***	-0.419***	0.832***	0.449***	1.000
Observations	1583									

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.